EDUCATION AND INVENTION

Otto Toivanen and Lotta Väänänen*

Abstract—Modern growth theory puts invention on the center stage. Inventions are created by individuals, raising the question of whether we can increase the number of inventors. To answer this question, we study the causal effect of MSc engineering education on invention, using data on U.S. patents' Finnish inventors and the distance to the nearest technical university as an instrument. We find a positive effect of engineering education on the propensity to patent and a negative OLS bias. Our counterfactual calculation suggests that establishing three new technical universities resulted in a 20% increase in the number of USPTO patents by Finnish inventors.

I. Introduction

A cornerstone of much of recent growth theory is that ideas, being nonrival in nature, are a key source of growth (for surveys, see, e.g., Jones, 2005, and Aghion & Howitt, 1997, 2009). Furthermore, ideas are produced by human capital. The central consequence of this line of thinking is aptly summarized by Charles Jones (2005, p. 1107): "The more inventors we have, the more ideas we discover, and the richer we all are." This immediately leads to the following policy question: (How) can the number of inventors be increased? We seek to contribute to answering this question by studying the causal effect of education on invention. Education has been linked to growth in previous empirical work at the macrolevel,[1] but to the best of our knowledge, we are the first to address the question at the microlevel and focus on the link from education to individuals' propensity to patent inventions.

Both stylized facts and government policies support the view that education drives inventions and growth. First, both in cross section and over time, GDP per capita and levels of education are positively correlated. Second, societies invest increasingly large amounts (Freeman, 2010) in education—educational investments are typically 3% to 6% of GDP[2]—suggesting a strong belief in the existence of a causal link between education and growth. Third, some rapidly developing countries, notably China and India, have singled out science and engineering education as a way to foster future growth. This is documented in figure 1, which displays the number of science and engineering graduates in selected countries (due to lack of data on the former, only the latter for India).[3] The two countries showing a notable increase are China and India. In terms of comparing levels, it is interesting that these two countries outpace others, especially allowing for the fact that for India, only engineering graduates are included in the data. Finally, the fact that the United States has dropped in rankings in science and engineering graduates, in both absolute and relative terms, has led to alarm being raised in the United States together with some analyses on how to react to this (see, e.g., Burrelli & Rapoport, 2009; Freeman, 2006, 2010).[4]

We study the effect of individuals' education, concentrating on university (master's level or higher) engineering education, on their inventive productivity as measured by patents, and the quality of the patent. We use data on U.S. (USPTO) patents matched to individual data on (essentially) the entire Finnish working population over the period 1988 to 1996.[5] Previous descriptive studies using data on individual inventors have shown that inventors tend to be highly educated. Giuri et al. (2007) report that 77% of European inventors in the PatVal survey have a university degree and 26% have a doctorate. In our data, about 35% of the inventors have a master's degree, and 14% have a doctorate (see table 1). Onishi and Nagaoka (2013) show that having a doctorate degree is associated with higher patent productivity, while Hoisl (2007) finds no relation with education and inventor productivity.[6] In addition, our data show that the majority of Finnish inventors have an engineering degree (66%), indicating that the field of education

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* Toivanen: Aalto University School of Business, KU Leuven and CEPR; Väänänen: independent researcher, Finland.

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[1] The current consensus (see recent surveys by Sianesi & Van Reenen, 2003; Stevens & Weale, 2004; and Krueger & Lindahl, 2001) seems to be that there is at best weak empirical support for the causal relation between education and growth. Aghion et al. (2009), using U.S. state-level data, provide evidence of a causal link between education and growth (see also Vandenbussche, Aghion, & Meghir, 2005).

[2] See WDI education indicators at http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2_9.pdf.

[3] The reason for this is that we did not manage to find comparable data on Indian science graduates. One India Science Report (Shukla, 2005, in table 2.3) notes that the ratio of science to engineering students is three to one.

[4] See "Worrisome Trends" (2010): "The state of the science and engineering (S&E) enterprise in America is strong, yet its lead is slipping, according to data released at the White House January 15 by the National Science Board (NSB)." In the same issue, the assistant director for federal research and development, Kei Koizumi, is quoted as saying, "U.S. dominance [in science, technology, engineering, and mathematics] has eroded significantly." See also the recent report by the Task Force on the Future of American Innovation. In its list of "signs of trouble," the authors mention as first that "undergraduate science and engineering degrees within the U.S. are awarded less frequently than in other countries." Among countries with higher rates, they mention Finland. For a less alarmist view, see Gereffi et al. (2008), who argue that quality is more important than quantity.

[5] Obtained from the NBER patents and citations data file (Hall, Jaffe, & Trajtenberg, 2002).

[6] Jones (2009) provides a model that explains changing patterns in inventor behavior, related to, for example, specialization and teamwork.

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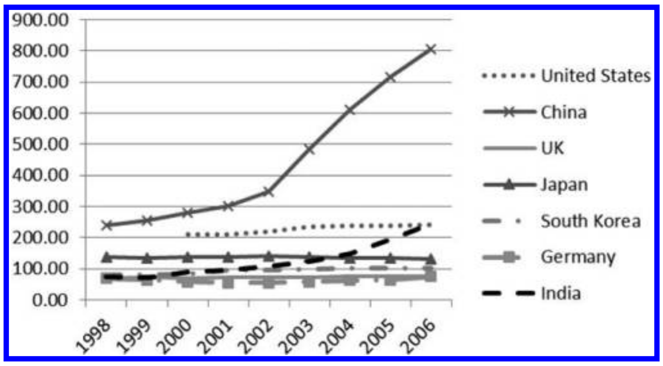
Figure 1—Science and Engineering Graduates in Selected Countries



Source: For all countries but India, NSF, 2010 (figure O-8). See http://www.nsf.gov/statistics/seind10/figures.htm. For India, the source is Banerjee and Muley (2008).

is also associated with patented inventions.[7] This observation is in line with Murphy, Shleifer, and Vishny (1991) who report some evidence that countries with a higher proportion of engineering college majors grow faster. While existing evidence thus suggests a significant positive association between individuals' education and their inventiveness, the causality of this link remains unexplored. Understanding the reasons for the positive association is important. If it is solely caused by selection, then education merely functions as a screen, but is not increasing the inventive potential of an economy. The question is how to attract the right individuals at the lowest social cost to education. If, in contrast, there is a causal impact, then education indeed increases the inventive potential of an economy. The question then is about the socially most beneficial form and availability of education. These two sources of positive association between education and invention thus have different implications for policy.

We identify the causal effect of university engineering education on the propensity to patent by using geographic variation and over time in the possibility of obtaining a university engineering degree. During the 1960s and 1970s, Finnish education policies led to a large increase and geographic widening in the possibility of obtaining a university engineering degree. We use these changes as a quasi-natural experiment in the spirit of papers that use the distance to college as an instrument in studying the returns to education (surveyed by Card, 2001) and of papers that use the schooling reform implemented in all Nordic countries in the 1960s and 1970s to study the effects of education on various outcomes (Meghir & Palme, 2005; Pekkarinen, Uusitalo, & Kerr, 2009). We link the individuals to the distance to the nearest university offering engineering education and use this as an instrumental variable for the individuals' schooling choice. A potential problem with this identification approach is that university location is affected by the same unobservables as our outcome variable. As we discuss

[7] In the macroeconomic literature on the relationship between education and growth, there is some work seeking to differentiate the impact of different levels of education on growth. See Aghion and Howitt (1997).

Table 1.—Descriptive Statistics for the Inventors and a Random Sample of the Population

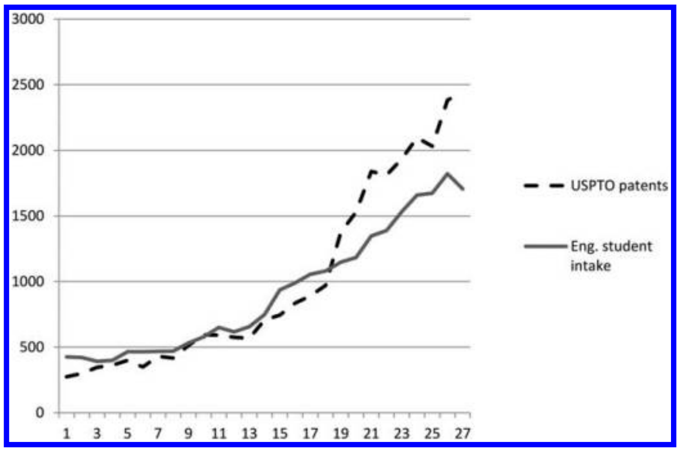
	Inventors	Other
Number of observations	2,328	66,530
Level of education		
Upper secondary	14.4	37.8
Lowest tertiary	11.0	13.0
Lower-degree (bachelor's)	18.0	5.4
Higher-degree (master's)	35.4	5.2
Doctorate	13.6	0.4
Unknown	7.6	38.3
Field of education		
General	5.5	4.4
Teacher education	0.3	1.9
Humanities and arts	0.6	2.0
Social science and business	2.7	11.9
Natural sciences	11.2	1.2
Engineering	65.9	22.2
Agriculture and forestry	1.6	3.4
Health and welfare	4.0	6.6
Services	0.8	8.2
Unknown	7.6	38.3
University engineering (master's or doctorate)	33.1	2.2
Age (years)	37	39
Female	7.9	49.3
Finnish speaking	92.6	94.1
Swedish speaking	6.5	5.4
Birth cohort		
1931–1950	43.5	51.2
1949–1960	41.3	35.3
1959–1964	15.2	13.5
Labor market status		
Employed	95.7	83.6
Unemployed	0.6	4.1
Student	1.8	1.8
Retired	0.5	5.4
Other	1.5	5.1
Entrepreneur	6.4	11.9

The numbers are percentages, except for age, which is in years.

in more detail below (see section IIE), the process through which Finnish universities' location was determined in the twentieth century seems to involve strong political elements that are uncorrelated to the economic and inventive activity of potential university locations. This suggests that it is plausible to treat the location and time of establishment of (the new technical) universities as exogenous.

Using Finnish data seems pertinent to the study of the effect of education on invention for two reasons. First, as documented by, for example, Trajtenberg (2001), Finland is among the nations that have accomplished a transformation from a resource-based to an invention-based economy. This is reflected in the large increase in Finnish patent applications to the USPTO in the past two decades. Second, while the increased availability of higher education is a widespread phenomenon among the developed countries, this development in Finland is different from that in other countries in two respects. The first one is the scope of this change: the proportion of a cohort to whom there are higher education study places is among the highest in the world (OECD, 2008). The second is that the Finnish enlargement of the higher education sector has had a strong emphasis on increasing the availability of engineering education. During the 1950s to 1970s, three new universities offering engi-

Figure 2—USPTO Patents and Engineering Student Intake at Universities



The USPTO patent series is for 1981 to 2007 and the engineering student intake series for 1951 to 1977.

neering education were established in different regions of Finland to complement the two established technical universities. The share of engineering in higher education has traditionally been quite high in Finland. In 1950, engineering students accounted for about 15% of all new university students. While this share fell between 1950 and 1965 to 9%, there was renewed focus with the establishment of the universities, and the share moved back up to 15% by 1981. By way of contrast, in the United States, the proportion of graduate students studying engineering was around 5% between 1975 and 2005 (NSF, 2006, table 1). Among OECD countries, Finland stands out as the one with the highest emphasis on engineering: 27% of the Finnish working-age population with a tertiary education has a degree in engineering, whereas the OECD average is 15% (OECD, 2008). Given that engineering is the form of higher education that is most directly targeted toward industrial R&D, one could view the Finnish education policy as an experiment whose individual-level treatment effect we seek to identify and from which other countries may learn.

To demonstrate these facts further, we show in figure 2 the number of USPTO patents, and the annual intake of engineering students at Finnish universities. Note that the two highly correlated graphs (correlation coefficient 0.98) are from different periods: The patent series is from 1981 to 2007 and the intake of engineering students from 1951 to 1977. While the (choice of) timing of the time series is obviously open to criticism,[8] it demonstrates that at the aggregate level, there is some reason to think that there could be a relationship between a policy that was implemented from the 1950s to the 1970s and outcomes measured in the 1990s.

By way of preview of our results, our Wald estimates that use the (different changes over time in the) regional variation in the distance to the nearest technical university show a positive treatment effect. In the IV estimations, the first-stage results show that the distance to the nearest university offering engineering is a good predictor for getting such degree. The estimated effect of a university engineering degree on individuals' propensity to patent is positive and significant, with a coefficient of 0.15 (0.3 for the patent count). This is about 2.5 times as large as the OLS estimate. We thus find a strong negative selection bias in the OLS estimations. The direction of the bias suggests that the costs of education to an individual are driving selection and therefore that lowering the barriers (in particular, reducing distance-related costs) to university education may be an effective policy tool in attracting to formal (tertiary, engineering) education inventive individuals who would otherwise have chosen something else.[9] We find some evidence that the estimated treatment effect is the average treatment effect on the treated instead of a local average treatment effect. Our back-of-the-envelope counterfactual calculation, where we look at what would have happened if the new engineering universities had not been established, shows that the number of USPTO patents assigned to Finnish inventors would have declined by some 20%.

We proceed as follows. In section II, we describe the data and discuss the politics of Finnish university location. In section III, we present the empirical framework and discuss the identification strategy. In section IV, we present the results, including robustness tests designed to check whether our results are sensitive to omitted variables that are correlated with both university location and inventive outcomes and to the functional form used for the instrument in the first-stage regression. Section V contains the counterfactual analysis and section VI the conclusions.

II. Data and Descriptive Analysis

A. *Data*

Our data come from several sources. Information on inventors and USPTO patents comes from the NBER patents and citations data file described in Hall, Jaffe, and Trajtenberg (2002). We match these data to the Finnish Linked Employer-Employee data of Statistics Finland (FLEED), a register-based data set that contains detailed information on the population of Finnish working-age individuals and their employers.[10] Third, we use the Finnish 1970 census to add information on the parents of the individuals in our sample. Finally, we match the patent data to data on the universities and student intake in engineering in the years 1950 to 1981, obtained from the Finnish Educational Establishment Statistics, and obtain a matrix of intermunicipality driving distances from the Finnish Road Administration.

[8] The qualitative message of the figure is robust to different timing choices. Naturally, the figure implies nothing about causality.

[9] That is, we identify the (weighted) local average treatment effect on the "compliers," those individuals who were prompted to enter university engineering education by a shift in the instrument we use. See chapter 25 in Cameron and Trivedi (2005) or section 6.3.2 in Imbens and Wooldridge (2008).

[10] The FLEED is described in Korkeamäki and Kyyrä (2000).

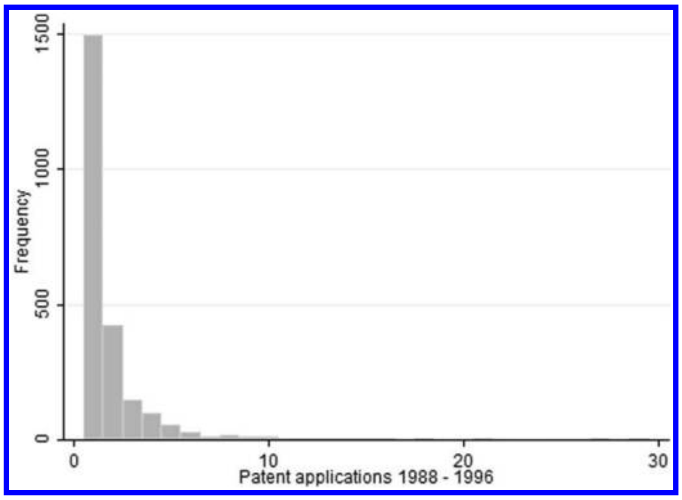
Briefly, the process of matching the inventors from the patent records to FLEED was as follows.[11] To identify the individuals, the information contained in the patent records (name of individual, and address, at least the municipality, at which the individual resided at the time) was used to search the Finnish Population Information System for the identification codes of individuals who matched these data. In case there was more than one match, we picked the individual whose employer's name in the FLEED matched the patent assignee in the USPTO data (at the time of application). If this process failed to identify a single individual, we excluded such individuals from our data. Out of the 8,065 inventor-patent records we were able to match 5,905, consisting of 3,253 individuals.

The Finnish Educational Establishment Statistics are available for each year from 1945 onward. They contain information on all the higher education establishments, including the type of the establishment and fields of education, size (by number of students), and geographical coordinates. We concentrate on engineering education at universities because the inventors in our data are predominantly, if unsurprisingly, engineers with a university degree.[12] We also conduct the analysis, however, using engineering education in general (including college-level engineering) and general university education as alternative measures of education. For each individual, we measure the distance from each engineering establishment (in the year of the individual's eighteenth birthday, to represent the relevant year of making the schooling choice) to the individual's birthplace.[13] The distances we use are road driving distances from the Finnish Road Administration. We also measure the student intake in each of the establishments relative to the size of the potential applicant cohort as an alternative measure.

B. The Sample

To construct the sample, we take a cross-section of individuals in the year 1988, who were born between 1932 and 1963. These individuals made their schooling choices in the years 1950 to 1981, under the assumption that they did so when they were 18 years old. In addition to all the individuals identified as inventors in the time period 1988 to 1996 (2,328 inventors), our data include a random sample of working-aged individuals (noninventors) from the FLEED, which contains the full Finnish working-age population.[14]

Figure 3—Histogram of the Patent Count for the Sample of Inventors



We take a 5% random sample from the 1988 cross-section for our analysis, after which we keep the observations for individuals born between 1932 and 1963. Our sampling weights are the inverse of the sampling probability (1/0.05), that is, a weight of 20 for each of the control observations. Thus, the sampling procedure we use is choice-based sampling, with separate random samples for observations with $Y = 0$ and $Y > 0$.

C. Descriptive Statistics

Table 1 shows the means, measured in 1988, for the key variables for inventors—individuals who were inventors in a patent applied in any of the years 1988 to 1996, as well as for a random sample of the Finnish working-age population. The table shows that there are several characteristics according to which the inventors are different from the rest of the working-age population. They are more likely to be men (only 7% are women); they are highly educated—much more likely to have completed their high school matriculation and have a university education (a bachelor's, master's, or doctoral degree); and they are more likely to have their education in the fields of natural sciences and engineering. Finally, we note that they are particularly likely to be university-educated engineers (33% of inventors compared to 3% of the random sample).

In figure 3 we present histograms of the number of patents per inventor over the period 1988 to 1996. The great majority of the inventors (60%) have just one patent over the full time period, about 20% have two patents and very few have more than five patents.

Next, we explore the association between different types of education and patent output and run an OLS regression with 46 dummies for the level-field combinations of education. We use weights in the regression to adjust for the sampling procedure. As control variables, we include in our estimating equation indicator variables for gender, nationality (Finnish, foreign), language (Finnish, Swedish, other), and birth year. While most coefficients are small in absolute

[11] The matching process is described in more detail in Toivanen and Väänänen (2012).

[12] In Finland, a university engineering degree is a five-year master's degree. Engineering colleges offered a four-year degree that is equivalent to a bachelor's degree (there was a reform of universities in Finland in the mid-1990s, and now the degrees are somewhat different). There is also a large fraction of college engineers in the data; thus, we use both definitions in our analysis.

[13] Municipality of residence at the time of the schooling choice would be preferred but is unavailable.

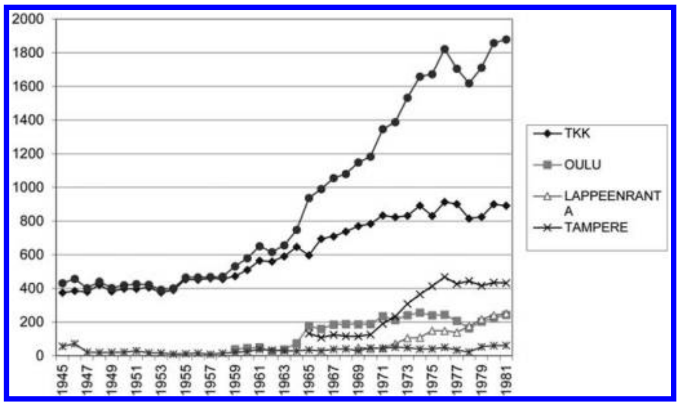
[14] Our data contain no foreign-born individuals, and we can therefore link every individual in the sample to his or her father and the father's education.

Table 2.—OLS Coefficients of Fields of Education

	Upper Secondary	Lowest Tertiary	Bachelor's	Master's	Doctorate
Teacher education	−0.003***	−0.001**	−0.002***	−0.003***	−0.003***
	0.000	0.001	0.000	0.000	0.001
Humanities and arts	−0.002***	−0.003***	−0.003***	−0.002***	−0.003***
	0.001	0.000	0.000	0.001	0.001
Social science and business	−0.002***	−0.002***	−0.002***	−0.003***	−0.004***
	0.000	0.000	0.001	0.000	0.000
Natural sciences	0.000	−0.004***	−0.001	0.043***	0.145***
	0.003	0.000	0.001	0.006	0.026
Engineering	−0.003***	0.006***	0.026***	0.093***	0.291***
	0.000	0.001	0.003	0.007	0.050
Agriculture and forestry	−0.004***	−0.004***	−0.004***	0.004*	0.040*
	0.000	0.000	0.000	0.002	0.024
Health and welfare	−0.002***	−0.002***	−0.001	0.003*	0.105***
	0.000	0.000	0.001	0.001	0.025
Services	−0.003**	−0.003***	−0.003***	−0.004***	0.044
	0.000	0.001	0.001	0.001	0.064

The dependent variable is the sum of patents of individual *i* in the period 1988 to 1996 (Patent Count) obtained by this individual. The table shows the estimated coefficient and standard error. Significant at ***1%, **5%, *10%. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. The base category is general education.

Figure 4—Number of New Engineering Students at Each of the Universities



size, we find significant and large differences between different fields and levels of education. Table 2 shows the coefficients of the education dummies from the OLS regression. We see that engineering education has a positive significant coefficient at all levels of education but the lowest, with the magnitude increasing with the level of education.[15] At the master's and the doctoral level, the coefficients for the natural sciences are large and significant. At the doctoral level, the coefficient of the health and welfare field is also large and significant.

D. Data on Engineering Education

In this section we present the data we use to generate our instrumental variable. Figure 4 shows a graph of the number of new engineering students in each of the Finnish universities that offered engineering education during the period 1945 to 1981. In 1945, two universities were offering engineering education, both in southern Finland: the largest one in Helsinki (TKK) on the south coast[16] and a small Swedish-speaking one in Turku (Åbo Akademi) in the southwest corner of the country. Together they had just over 400 new students starting that year. In 1959, the University of Oulu (over 600 kilometers from Helsinki) in northern Finland began to offer engineering education, followed by Tampere in southern Finland (176 kilometers from Helsinki) in 1965 and Lappeenranta in eastern Finland (221 kilometers from Helsinki) in 1969.[17] From 1960, there has been rapid growth in the total number of new engineering students at universities, tripling from 600 to 1,800 in less than twenty years. While the Helsinki University of Technology doubled its student intake in engineering in the period 1945 to 1981, the universities in the other regions also grew significantly.

In figure 5, we show the Finnish map, with the locations of the technical universities and their distance to Helsinki highlighted. The figure demonstrates how the establishment of the new universities changed considerably—even allowing for the fact that the Finnish population is concentrated in the south and southwestern parts of the country—the distance to the nearest technical university for a large majority of the Finnish population.[18] The distance between the

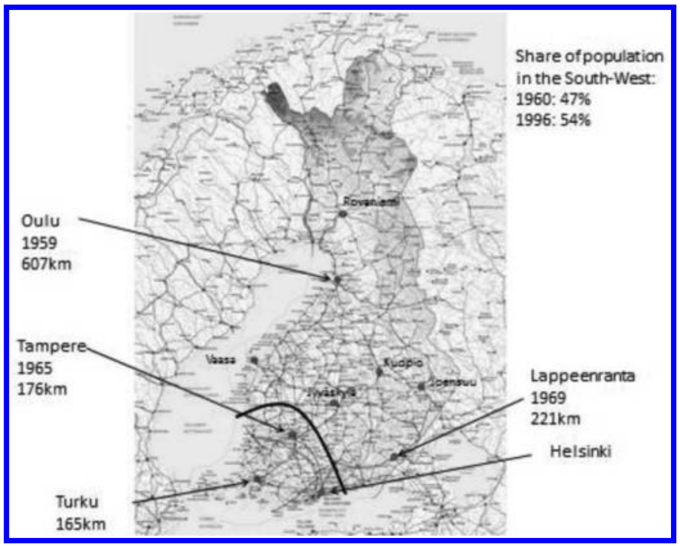
[15] Here it is interesting to note that according to the NSF (2009, chap. 3), in the United States 53% of individuals who hold a science and engineering degree and report R&D as a major work activity have a bachelor's degree as their highest degree. Only 12% have doctorates.

[16] TKK moved from Helsinki to neighboring Espoo starting in the late 1950s. The move was completed in 1966. The capital region of Finland consists of several independent cities and municipalities, the two largest of which are Helsinki and Espoo. This move obviously had only a very minor impact on the distance to the nearest technical university.

[17] Other universities, not offering an engineering education, were also established in cities shown on the map in figure 5. Jyväskylä's teacher's college obtained the right to grant doctoral degrees in 1944 and established the Faculty of Philosophy in 1958. The planned University of Eastern Finland was initially split into three, one of which is the technical university in Lappeenranta: the University of Joensuu was established in 1970 and the University of Kuopio in 1972. These two merged in 2010. The University of Vaasa on the west coast was established in 1968 and started to offer an engineering education in 1988 (too late to affect the educational choices of the individuals in our sample). Finally, the University of Lapland was established in Rovaniemi in 1979.

[18] This concentration has increased over time. In 1960, the three southern/southwestern regions (*lääni*) of Uusimaa, Turun ja Porin lääni, and Hämeen lääni housed 47% of the population. In 1996, the figure was 54%.

FIGURE 5—MAP OF FINLAND, WITH LOCATIONS OF ENGINEERING UNIVERSITIES AND DISTANCES TO HELSINKI



Universities that did not offer engineering education before 1988 were established in Jyväskylä (1944), Vaasa (1968), Kuopio (1972), Joensuu (1970), and Rovaniemi (1979).

"old" technical universities in Helsinki and Turku is 165 kilometers. The new technical universities in Tampere, Lappeenranta, and Oulu are clearly inland, to the east, and north of the old technical universities. Our instrument builds to a large extent on this geographic and over-time variation in where university-level engineering education was available.

A potential weakness of this instrument is that the location of universities is not random.[19] We next discuss the processes through which the locations and time of establishment of different universities were determined.

E. Location Decisions of the New Universities

The first Finnish technical university was established in the capital, Helsinki, in 1909 where the only university already resided. However, already since the mid-ninteenth century, there has been a heated discussion on where outside Helsinki to locate a new university (Tommila, 2002). The discussion revolved around four points: the need for new universities; the choice between general, multidisciplinary universities and more specialized (e.g. technical) universities; the need to centralize or decentralize university education; and the language question, referring to the then-dominance of the minority Swedish language in higher education. As early as in the 1850s, suggestions were made to split the University of Helsinki and relocate its parts around the country. Essentially all major cities expressed interest sooner or later, and local associations were established with the aim of influencing the university location decisions.[20]

The process through which Abo Akademi in 1918 (when it was established) got a technical faculty provides a parallel for postwar decision making. To the very end, it was unclear which faculties would be included, but finally, the technical faculty was among them, despite resistance from the technical university in Helsinki and disagreement among the founders.

More important for our exercise, the establishment of the engineering faculty at the University of Oulu and the technical university in Lappeenranta provides a window into the determinants of location.[21] A committee for the establishment of a university in northern Finland suggested Oulu as the location in 1956, with a plan for starting with faculties of philosophy, engineering, and medicine. The Ministry of Trade and Industry fiercely opposed the establishment of an engineering faculty, as did the Technical University in Helsinki. In the end, the committee's suggestion prevailed in this respect (Eskola, 2002a).

The Technical University in Lappeenranta was born out of a complicated political process. There was more or less agreement that eastern Finland needed a university, but that is where the agreement ended. All major cities in the region lobbied to be chosen. A committee suggested in 1961 that a university should be established in Lappeenranta with faculties of engineering and humanities. The committee was, however split, with Lappeenranta getting four, Kuopio three, and Joensuu one vote, and with one member abstaining from the vote and disagreeing with the suggestion (Eskola, 2002b). Kuopio, Joensuu, and the city of Savonlinna started a heavy lobbying process to influence the government, and in the same year, a suggestion was made to split the university. A committee was established. It submitted three reports and concluded that "the committee has been unable to find justifications for preferring one location over the others."[22] The committee suggested establishing a technical university in Lappeenranta (and in Tampere), with other faculties going to other cities. Lappeenranta lobbied to get the entire university and the other cities for Lappeenranta to get nothing. The government was openly split on the matter, with the prime minister backing the committee's proposal and the minister of education opposing it. Finally the government voted and decided to establish three universities—one each in Kuopio (founded in 1972), Joensuu (1970), and Lappeenranta (1969), with the last one getting the technical university. The process was thus long and of

[19] This goes back to at least Marshall (1890): "When an industry has thus chosen a locality for itself . . . the mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously."

[20] To mention just one suggestion, a prominent participant in the discussion suggested in 1917 that the new university should be split between the cities of Turku, Tampere, Jyväskylä, Lahti, Viipuri, and Oulu. Today all but Lahti (and Viipuri, which was lost to the Soviet Union in World War II) have a university. Several cities with university associations failed to get a university (e.g., Hamina, Rauma, and Hämeenlinna).

[21] Here we lean heavily on the apparently aptly named chapter "The Fight over the University of Eastern Finland" (Eskola, 2002b), in Tommila and Tiitta (2002).

[22] See Eskola (2002b, p. 238) (our translation).

uncertain duration, erratic, and the decision unclear to the very end.

No discussion of invention in Finland is complete without discussing Nokia. Most of Nokia's R&D is located in Helsinki and Oulu. Whereas it is clear that the technical university in Helsinki was established well before Nokia's move into electronics, one may wonder whether the company's location in Oulu provides evidence countering our assumption of university location being exogenous to inventive activities. However, evidence provided by Oinas-Kukkonen et al. (2005) suggests otherwise. According to Oinas-Kukkonen et al., the Institute for Information Processing Science was established at the University of Oulu in 1968–1969. Professor Matti Otala joined the university from Nokia in 1967, and the first Nokia factory in Oulu was established in 1974. It thus seems that while a major part of the human capital that drew Nokia to Oulu had a Nokia connection (Otala), it was the human capital at the university that drew Nokia to Oulu rather than the other way around.[23]

One way to check whether university location is driven by underlying differences in inventiveness is to look at differential trends in enrollment to engineering studies at university locations as opposed to other locations (farther away) before the establishment of the university. We checked this for Oulu. It turned out that enrollment from the Oulu area to university engineering studies was practically zero prior to the establishment of the University of Oulu and the simultaneous establishment of the engineering faculty. This suggests that there was no nascent engineering trend in Oulu that would have led to the government's choosing Oulu as the location.

Given this background, it seems to us that the decision of whether a city got a university, or whether the university ended up providing engineering education seems to have been open to the very end of each process. Furthermore, the durations of the decision-making processes seem to have been highly uncertain. It also seems that in the end, the decision was largely determined not by economic and technical issues but for political reasons. We therefore think that it is reasonable to treat the location and year of establishment of (technical) universities as exogenous in our analysis.

III. The Empirical Framework

We estimate the effect of engineering higher education on individuals' inventiveness, as measured by their total patent output (USPTO patents by application date) over the period 1988 to 1996. We use a linear specification and estimate equations of the following form:

$$Y_i = \alpha + \beta X_i + \theta ENG_i + \varepsilon. \tag{1}$$

Y_i is our output measure (a 0/1 indicator for patents granted to individual i, sum of patents granted to individual i, or citations received by the patents of individual i), X_i are control variables describing the individual (gender, cohort dummies, native tongue), and ENG_i is an indicator equal to 1 if the individual has obtained a university engineering degree (master's or doctorate) by the year 1988. θ is the key parameter of interest, measuring the (weighted) local average treatment effect (see Imbens & Wooldridge, 2008) of engineering education on inventive output, and β is a vector of parameters on the control variables.

The error term in equation (1) may be correlated with the schooling measure and patents due to, for example, omitted variables related to unobserved individual ability, as in estimating the returns to schooling. However, it is not clear ex ante what the direction of the omitted variable bias is because the unobserved ability affecting the propensity to patent (individual's inventiveness) is not necessarily positively correlated with the ability that is typically thought to increase an individual's net benefits from schooling. In other words, individuals with low (effort) costs of studying could on average be less good at creative thinking that leads to invention, leading to a negative correlation and downward bias in the OLS estimate.

In addition, there may be an issue of essential heterogeneity or selection on gains, which generates positive correlation between schooling and the error term. If engineering higher education increases the propensity to patent, but mainly for individuals with innate inventive ability, then those individuals have a higher additional benefit of schooling in terms of their increased propensity to patent and are thus more likely to choose such schooling.

We apply instrumental variables for the individuals' schooling choice and identify the (weighted) local average treatment effect (LATE) for individuals who are affected by the instruments we use. We discuss our identification strategy and our instrumental variables in the next section.

A. *Identification*

We borrow the idea of using (time-varying) geographic variation from the literature that uses educational reforms to estimate, for example, the returns to education (Card, 2001; Meghir & Palme, 2005). Moretti (2004) uses the establishment of land grant colleges in the nineteenth-century United States to estimate human capital spillovers using 1980s data. The quasi-experiment we use is the growth of the Finnish university-level engineering education system that took place between 1950 and 1981. This variation allows us to adopt an instrumental variable approach.

Individuals choose their education by evaluating the costs and benefits of the alternatives. We use instruments generated from exogenous factors that affect individual's cost of choosing an engineering education. Using individuals' birth year and place, we determine the distance to

[23] As a final note on Nokia, we cannot check the robustness of our results to removing Nokia employees from the sample because we cannot identify individual companies in the data. The problem with the alternative approach, which is to form a group of large R&D firms and interact this dummy with the instrument, is that job placement is endogenous.

and availability of university engineering education. These measures correspond to institutional variations on the supply side of the education system and are typical of the kind of instrumental variables used in the recent literature studying the effects of schooling choices on labor market outcomes (Card, 2001).[24] We combine distance-based instruments (geographical variation) with cohort-based instruments (over-time variation).

Our instrumental variable is based on distance, which exogenously generates variation in individuals' mobility costs. Individuals, depending on where they live, face different costs of traveling or moving to a town where engineering education is offered. Our identifying assumption is thus that the distance between the location of an individual and the nearest technical university affects the probability of obtaining a university-level engineering degree, but does not directly affect the propensity to patent (or the quality of the patents, measured by citations).

This instrument mainly has geographical variation, but there is also some variation over cohorts, as three new universities are founded at different times during the time period. When using a location-based instrument, it is important to control for other factors that are correlated with the location. For example, families living in or near university towns are different from those living in smaller towns and rural areas, and family background can influence both schooling and inventiveness. We control for the level and field of the father's education at a very detailed level, measured in the year 1970, the first year for which such data are available.[25] Our measure of father's education has two dimensions: field of education and level of education. Regarding the former, we have eight types of education, ranging from humanities and arts to agriculture and forestry. Regarding the latter, we have up to six levels of education for each type of education, ranging from lower secondary to doctorate or equivalent. We observe father's education for 56% of the estimation sample. We present the descriptive statistics on father's education in the online appendix.

The treatment effect we identify is LATE for individuals affected by the instruments we use. As our instruments generate variation in the costs of choosing university engineering education, the individuals affected by the instrument are those who are at the margin of choosing university engineering education over some other schooling choice. It is important to note that it is unclear what the relevant counterfactual is—that is, what the individuals would have chosen had they not chosen university engineering education. We can only make a guess that the relevant next best choice for this group is either a lower-level engineering degree or a university degree in some other field.

The LATE we identify is a relevant variable from the policy point of view. Viewing our instruments as being generated by variation in government educational policy, we are identifying the effect of this policy, to the extent that the policy can be represented by the location of universities.

IV. Results

We estimate the effect of university engineering education on individuals' propensity to patent, measured by the sum of their USPTO patent output over the time period 1988 to 1996. We begin by presenting simple difference and Wald estimates of the establishment of the three new universities in the provinces where they were established. We then move on to the regression analysis.

A. *Wald Estimates*

Table 3 presents simple difference and Wald estimates of the establishment of the three new universities in the provinces where the universities were established. The benefit of the Wald estimates is that they use in a straightforward manner the differential variation over time in the availability of university engineering education at different locations. For each province, we look at groups of nine birth cohorts before the establishment of the university and the nine cohorts after. As a comparison, we always look at the Uusimaa province (where the nation's largest technical university existed throughout the period) over the same time period.[26] We report the fraction of the cohort of 18-year-olds born in the province who are inventors (i.e., obtain a USPTO patent between 1988 and 1996) and engineers (higher-level college or university engineering degree) before and after the establishment of the university.

In panel A, we look at the Pohjois-Pohjanmaa province (for the years before 1950 to 1958 and after 1960 to 1968), where a technical university was established in Oulu in 1959. The fraction of engineers increases from 0.7% to 2.2%, while the fraction of inventors increases from 0.04% to 0.19%. During the same period, there is also rapid growth in the fraction of engineers in the Uusimaa cohorts (as Helsinki University of Technology also experienced an increase in student intake), from 3.4% to 5.7%, and the fraction of inventors goes up from 0.18% to 0.27%. The Wald estimate of 0.09 for Pohjois-Pohjanmaa indicates that about one-tenth of the engineers became inventors. For Uusimaa, the estimate is only about half the size, around 0.04. Thus for Uusimaa, where the initial level of engineers is higher, further increases appear to produce fewer inventors on average.

[24] Kelchtermans and Verboven (2010) and Frenette (2009) study choice of higher education institutions. The former use a funding reform in Belgium (Flanders) and the latter the establishment of new universities in Canada. Both studies find that distance plays an important role in the choice of what to study and where.

[25] Unfortunately, we know neither the identity of the university an individual attended nor the locations of the relatives of individuals; hence, we cannot control for an individual having relatives in a particular university city.

[26] The Uusimaa estimate is thus not a Wald estimate, as the instrument (i.e., distance to the nearest technical university) does not change.

TABLE 3.—WALD ESTIMATES

Panel A	1950–1958	1960–1968	Difference	Wald
Pohjois-Pohjanmaa				
Cohort size	22,367	31,660		
Inventors	10	59		
	0.0004%	0.0019%	0.0014%	
Engineers	163	706		
	0.0073%	0.0223%	0.0150%	0.0944%
Uusimaa				
Cohort size	23,107	50,135		
Inventors	42	139		
	0.0018%	0.0028%	0.0010%	
Engineers	794	2,866		
	0.0344	0.0572	0.0228	0.0419
Panel B	**1956–1964**	**1966–1974**	**Difference**	**Wald**
Pirkanmaa				
Cohort size	29,088	34,142		
Inventors	53	96		
	0.0018	0.0028	0.0010	
Engineers	890	1,365		
	0.0306	0.0400	0.0094	0.1055
Uusimaa				
Cohort size	39,089	55,728		
Inventors	107	138		
	0.0027	0.0025	−0.0003	
Engineers	2,127	2,692		
	0.0544	0.0483	−0.0061	0.0427
Panel C	**1960–1968**	**1970–1978**	**Difference**	**Wald**
Etelä-Karjala				
Cohort size	13,769	13,857		
Inventors	14	22		
	0.0010	0.0016	0.0006	
Engineers	466	571		
	0.0338	0.0412	0.0074	0.0775
Uusimaa				
Cohort size	50,135	58,019		
Inventors	139	155		
	0.0028	0.0027	−0.0001	
Engineers	2,866	3,025		
	0.0572	0.0521	−0.0050	0.0201

The table shows the fraction of the cohort who are inventors and engineers both before and after the "treatment" of the establishment of a technical university in the province. In column 3, it presents the change in these, and in column 4th Wald estimate. Uusimaa province, where a technical university existed throughout the period, serves as the comparison group in each case. All estimates are given in both number and percent.

Looking at Pirkanmaa province (panel B) and the years 1956 to 1964 (before) and 1966 to 1974 (after the establishment of the technical university in Tampere), there is a relatively modest increase in the number of engineers (there already was an engineering college in Tampere before the University was established), but the increase in inventors is larger (in percentage terms). The resulting Wald estimate is 0.10 (notably similar to the figure for Pohjois-Pohjanmaa). For the same period for cohorts born in Uusimaa, the fraction of engineers in fact decreased, as did the fraction of inventors. The estimate is very similar to the one in the earlier period (0.04).

Finally, looking at Etelä-Karjala before and after the establishment of the technical university in Lappeenranta (panel C), we get a Wald estimate of 0.08, and for the same period comparison, the estimate for Uusimaa (where again both the fraction of engineers as well as the fraction of inventors decreased) is 0.02.

Altogether these results suggest that the increase in the number of engineers born in the provinces where new technical universities were established, obtaining their degree around the time of the establishment, is associated with larger increases in the number of inventors (born in these provinces) than the increase of inventors for cohorts born in Uusimaa, where a university already existed and the initial level was already high.

B. *Regression Analysis*

We run our estimations for three (second-stage) dependent variables (patent count, patent dummy, expected citations) and for three measures of education (engineering education, technical university education, and university education). Furthermore, we run these specifications with two sets of control variables (with and without father's education).

OLS estimations. Table 4 presents the estimated coefficients from the OLS estimations for our key variable of interest: a dummy variable indicating the type of education. The first column shows the results from the estimations based on a larger sample without controlling for family

TABLE 4.—OLS RESULTS

	No Family Background	With Father's Education
Patent count		
University engineering	0.110***	0.118***
	(0.007)	(0.009)
Engineering	0.0591***	0.0628***
	(0.003)	(0.004)
University	0.0316***	0.0348***
	(0.002)	(0.002)
Patent indicator		
University engineering	0.0493***	0.0517***
	(0.003)	(0.003)
Engineering	0.0282***	0.0296***
	(0.001)	(0.001)
University	0.0144***	0.0156***
	(0.001)	(0.001)
Citations		
University engineering	1.179***	1.350***
	(0.101)	(0.132)
Engineering	0.618***	0.357***
	(0.045)	(0.029)
University	0.313***	0.707***
	(0.021)	(0.059)
Numbers of observations	60,234	33,645

The dependent variable is the sum of patents of individual *i* in the period 1988 to 1996 (patent count), an indicator for individual *i* obtaining at least one patent from 1988 to 1996 (patent indicator), or the citations to the patents obtained by individual *i*. The table shows the estimated coefficient and the standard error in parentheses.*** Significant at 1%. In all specifications, the control variables are gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

TABLE 5—FIRST-STAGE ESTIMATES

	No Family Background	With Father's Education
University engineering	−0.262***	−0.161***
	(0.029)	(0.061)
Engineering	−0.452***	−0.461***
	(0.047)	(0.096)
University	−1.08***	−0.378**
	(0.08)	(0.169)
Number of observations	60,234	33,645

The table shows the estimated coefficient and the associated standard errors in parentheses. Significant at ***1%, **5% level. Coefficients and standard errors have been multiplied by a factor of 100. The instrument is distance to the nearest technical university when the dependent variable is either the indicator for a university engineering degree or an engineering degree and distance to the nearest university when the dependent variable is a university degree. In all specifications, the control variables are gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

TABLE 6—IV ESTIMATES

	No Family Background	With Father's Education
Patent count		
University engineering	0.234***	0.302**
	(0.038)	(0.15)
Engineering	0.136***	0.106***
	(0.021)	(0.041)
University	0.067***	0.202**
	(0.009)	(0.104)
Patent indicator		
University engineering	0.108***	0.155**
	(0.015)	(0.068)
Engineering	0.063***	0.054***
	(0.009)	(0.017)
University	0.030***	0.093**
	(0.004)	(0.045)
Citations		
University engineering	2.322***	2.592
	(0.438)	(1.787)
Engineering	1.347***	0.907*
	(0.249)	(0.558)
University	0.736***	2.137*
	(0.117)	(1.213)
Numbers of observations	60,234	33,645
Control variables		
Father's education	No	Yes
Regional dummies	No	No

The table shows the estimated coefficient and the associated standard errors in parentheses. Significant at ***1%, **5%, *10%. In all specifications, the control variables are gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

background and the second column from the estimations with father's education included as a control (45 dummies for field-level combinations of education). This sample is smaller, as father's education is not available for all individuals. The smaller sample is also somewhat different with regard to the ages of the individuals, as for the older cohorts, it is more likely that the father was no longer alive in 1970 when we observe father's education.

The OLS regressions show, throughout the different specifications, that education, in particular university-level engineering education, has a positive and significant association with patenting. For the patent count as our dependent variable (the top panel in table 4), the coefficients on university engineering education range from 0.110 (SE, 0.007) to 0.118 (SE, of 0.009). The coefficients for engineering education in general (including college-educated engineers) are only about half this, and those for university education in general are even smaller. When using either a patent dummy (middle panel in table 4) or citations as the dependent variable (the lower panel in table 4), we obtain results that mirror the previous ones.

As discussed earlier, the endogeneity bias in the OLS estimates could be in either direction. This is what we investigate next using instrumental variables.

IV estimations. In the instrumental variable regressions, the results of which are reported in tables 5 and 6, we use the distance to the nearest university offering an engineering degree as our instrumental variable affecting the choice of engineering education. For the effect of university education in general, the instrumental variable is the distance to the nearest university (including universities that do not offer engineering degrees). Table 5 presents the estimated coefficients (and associated standard errors below) on the instrumental variable in explaining the individual's education type (first stage). Table 6 presents the IV estimates of the coefficients on the education dummy from the regressions on patent output. Similarly to the previous table, the first column shows the results from the estimations based on the larger sample without controlling for family background and the second column from the estimations including the 45 indicator variables for father's education.

Looking at columns 1 and 2 in table 5, we see that the distance to the nearest technical university has a significant negative effect on choosing such schooling, as expected. The coefficients on the distance (in 100 kilometers) are −0.0026 (without father's education) and −0.0016 (with father's education) for university engineering education. Given the average probability of choosing such education (0.022), this translates into about a 10% increase in the probability as distance decreases by 100 kilometers. We also see that our instrument is quite strong in both specifications, although somewhat reduced by controlling for father's education. Part of this reduction in the strength of the instrument is also due to the smaller sample in the regression with father's education; in the appendix we present the first-stage robust F-tests for the different samples and specifications. In the robustness section, we further probe the validity of the instrument and the effect of using polynomials of different order for the instrument in the first stage.

Table 6 presents the estimation results from the second stage of the IV estimations (i.e., the patenting equation). The estimated coefficients throughout the different specifications are 2 to 2.5 times the respective OLS estimates. This result could indicate a negative selection bias, meaning that those who have a high innate propensity for invention have a lower propensity to study at a technical university. This interpretation is, in a sense, in line with the instrument we use and the treatment effect we identify. Individuals who are induced to obtain a university-level engineering education as a result of the proximity of a university (our instrument) are at the margin and thus not those who have the highest net benefits. A cost-based explanation would be that among those with the same distance to the university, the ones with a lower cost of attending (larger shock in the first-stage participation equation) are less likely to invent (smaller shock in the second-stage invention equation). The LATE we identify is for the portion of the population affected by these distance-related mobility costs. From the specification in column 2 for the effect of university engineering education, the coefficient of 0.3 indicates that inducing individuals to choose this kind of education due to its proximity (affected by the establishment of the new universities) leads to increases in patent output; about three university engineers are needed to produce one extra patent.[27] Finally, if our instrument does not satisfy the exclusion restriction, the negative OLS bias would mean that the Marshallian co-location story is at work: those close to the university are more likely to invent regardless of whether they obtain an engineering degree.

Comparing the results across dependent variables reveals that the pattern discovered in the OLS estimations is replicated here, with the patent indicator yielding the smallest coefficients and the citation count the largest. When one compares the results across specifications, it is clear that the statistical significance of the estimated treatment effect tends to decline as we include the vector of father's education dummies as control variables. Finally, when comparing the three endogenous dependent variables (= measures of education), it is worth pointing out that the relative sizes of the coefficients are well in line with what the OLS estimates already suggested, with university engineering yielding the largest treatment effect estimate. The relative size of the engineering and the university education coefficients depends on whether we control for father's education: without controlling for it (column 1), the engineering coefficient is larger, whereas the university education coefficient is larger once father's education is controlled for.

An additional interesting finding concerns gender differences in inventive productivity. While the OLS estimates show a strong negative association between female gender and patent output, this effect disappears once the endogeneity of engineering education is taken into account.[28] A large majority of the engineers are men. This suggests that the observed gender difference in patent productivity is simply due to the different types of education chosen by women and men.

Robustness tests. We also performed a number of robustness tests. First, we introduced an interaction term between distance and father's education (a dummy equal to 1 if the father has a university degree and 0 otherwise). If better educated-fathers' offspring are differentially affected by distance, this instrument should capture that effect. The second-stage point estimates are very close to those reported, as are the significance levels.

Second, we included dummies for the twenty regions (maakunta) in Finland. These should capture unobservables that are correlated with inventiveness and university location, thereby ameliorating worries that omitted variable bias (or endogeneity of university location) affects our results. We added these region dummies to our specification that includes the vector of father's education dummies. A problem with the region dummies is that they reduce the significance of our distance instrument as they by design are correlated with it.[29] We display the results in the appendix for all combinations of education and invention output. We found that while our instrument loses power when we use university engineering education as our education variable (the first-stage F-test is 1.513; see table A.2, column 1), the results using either engineering education or university education are in line with those in table 6. The coefficient for engineering education is 0.185 (SE, 0.088; see table A.3, column 1) and for university education 0.157 (SE, 0.068; see table A.4, column 1), with first-stage F-test values above 7. The former is a little larger, the latter a little smaller than those in column 2 of table 6 where father's educa-

[27] We have checked that the difference in the samples between is not driving the differences in coefficients in columns 1 and 2 of table 6. When estimating the base specification (without controls for father's education) using the sample for which father's education is observed, we get results very similar to those reported in column 1.

[28] This is the case when we use university engineering or engineering education. When we use university education, the female dummy obtains a small negative and statistically significant coefficient (Coefficient, −0.006; SE, 0.001).

[29] A substantial part is due to our sample decreasing when we introduce further controls. The region dummies in general do not perform well, with most of them obtaining small and highly insignificant coefficients. As an example, when we regress the number of patents on university engineering education, none of the region dummies obtains a statistically significant coefficient in the second stage.

tion was already controlled for. Our results thus seem reasonably robust to introducing further regional controls.[30]

As a final robustness check regarding location, we clustered the standard errors at the municipal level. This produced standard errors that were very close to the robust standard errors.

We then turned to the issue of what functional form to use for the instrument. To study this, we estimated all models in table 6 using a polynomial of the distance instrument and varying the order of the polynomial from 1 to 8. The results are reported in the appendix for all combinations of invention and education measures, polynomials of the instrument, and all three specifications (base specification, adding father's education, and adding region dummies). We repeated the exercise using the natural logarithm of distance and report the results using all three education measures and the patent count as the measure of invention. With the base specification, the first-stage F-test is always high, and the education coefficients from the different instrument specifications are very close to each other. We see a slight decrease in education coefficient size when the order of the polynomial is increased. As an example, with university engineering as the measure of education and the patent count as the measure of invention, the coefficient goes from 0.136 with a first-order polynomial to 0.128 with an eight-order polynomial. When we add father's education and region dummies, the higher-order polynomials do not pass the Stock-Yogo weak instrument test; however, the education coefficients and their statistical significance are remarkably stable. As a whole, the results using higher-order polynomials repeat the results using only a linear instrument: using engineering and university education consistently yields a significant second-stage coefficient for all three specifications (base, adding father's education, and adding region dummies), while the coefficient(s) using university education lose statistical significance when region dummies are introduced. Using the natural log of distance (or its higher-order polynomials) yields very similar results as using linear distance. We conclude that our results are robust to the functional form of the instrument.[31]

In addition to these robustness checks, we attempted to use another instrument based on the student intake into technical universities and estimate a model where we allowed a separate effect for engineering and other university-level education, instrumenting the latter with distance to the nearest university. The new instruments proved to be weak, and we therefore do not report these exercises here.

C. *Tests for Heterogeneous Effects*

We test for heterogeneous treatment effects using a test suggested by Heckman, Schmierer, and Urzua (2009). We first run a probit regression to estimate the propensity score of having a university engineering degree. We use the same set of control variables as in our main specification, including father's education. We then include a polynomial of this propensity score, together with interactions of it with some of the controls, and test for nonlinearity of these terms. The results for a variety of specifications of the polynomial, reported in table 7, suggest that we cannot reject the null hypothesis of a homogeneous treatment effect.

TABLE 7—TESTS OF HETEROGENEOUS TREATMENT EFFECTS

	No Interactions p-Value	With Interactions p-Value
Second order	0.805	0.926
Third order	0.725	0.32

The table shows the p-values of the joint significance (F-) tests. In all specifications, the control variables are gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations. In column 2, we interact the instrument and its powers with nationality and native tongue dummies.

The implication of accepting the test results would be that the treatment effect we have estimated is the average treatment effect on the treated, not the (weighted), local average treatment effect. That would obviously alter, and make stronger, our policy conclusions. We return to this below in the counterfactual analysis. Our reading of the results is that we have some, but no overwhelming, evidence in favor of our estimate being an average treatment effect on the treated.

D. *Discussion*

Taken together, the analysis suggests that by increasing the geographic availability of university engineering education, Finland enticed young people to enter engineering education, ultimately making them more likely to patent. The negative selection bias that we report suggests that a feature of the policy may have been to entice "non-standard" (more inventive) individuals to enter into engineering higher education or that variation in costs (conditional on distance) drive selection.

Returning back to our Wald estimates, the finding of higher Wald estimates for the provinces where new universities were established is in line with the finding of an IV estimate that exceeds the OLS coefficient. The IV based on the distance to the nearest technical university derives its variation from the over-time and across-region variation due to the establishment of the new universities, the same variation used to calculate the simple Wald estimates. In fact, the magnitudes of the Wald estimates are also similar to the IV estimates (from the specifications with the patent dummy as the dependent variable). Also, the relative magnitudes are similar: The Wald estimates in each of the provinces are about twice as large as that for Uusimaa in the same time period (roughly by how much the IV estimate exceeds the OLS). Note that the Uusimaa (Helsinki University of Technology) estimates are OLS estimates, as (in

[30] We repeated this exercise for the other two invention variables, with very similar results.

[31] We again repeated this exercise for the other two invention variables, with very similar results.

contrast to the other provinces) there is no change in the distance to nearest technical university.

A potential problem with our identification approach is that university location is affected by the same unobservables as our outcome variable. As we discuss in section IIE, the process through which Finnish universities' location was determined in the twentieth century seems to involve strong political elements that are uncorrelated to the economic and inventive activity of potential university locations. This suggests that it is plausible to treat the location and time of establishment of (the new technical) universities as exogenous.

V. Counterfactual Analysis

Finally, we perform a counterfactual calculation (in the spirit of Ichimura & Taber, 2000, 2002), of total patent output in 1988 to 1996 had the three new technical universities not been established. We do this by estimating the main equation (patent count as the outcome), now including the distance to the nearest technical university as a direct explanatory variable. We calculate the predictions in the actual scenario (and sum them over all the individuals) and compare them to the scenario where everyone's distance is replaced by the distance to the technical university in Helsinki (Espoo, TKK). A comparison of the two scenarios using our specification with father's education included shows a predicted decrease in patent output of 19% without the establishment of the three new technical universities, meaning a 23% increase due to new universities. Specifications with different polynomials of the instrument show slightly smaller counterfactual reductions in patent output ranging from 12% to 19%, translating into increases between 14% and 19%.

A key question is what lesson our results, taken at face value, offer to policymakers. The central message that arises suggests that reducing the hurdles to university-level engineering education may indeed lead to an increase in inventive output. How then to achieve a lowering of the costs of an engineering education? It is not clear at all from our results that reducing the distance is the right policy tool everywhere, even though it seems to have worked in the postwar Finnish environment. Here, the different interpretations of the estimated treatment effect lead to different implications. If the estimate is an average treatment effect on the treated, the choice of the policy instrument is of much less significance. Any policy that leads to an increase in engineers will lead to 0.2 to 0.3 patents more per every new engineer. If instead the estimate is a local average treatment effect, then this increase in patenting will be obtained only if the implemented policy changes the behavior of the same part of the cohort choosing what to study, as the Finnish policy affected in the postwar period. Whether this will be the case is much harder to assess.

Finally, notice that our counterfactual analysis is back-of-the-envelope because we have not estimated a structural model. We thus do not know what the general equilibrium effects of the adopted policy were, or what would have happened if it had not been implemented. For example, our analysis does not shed light on what those individuals would have done who, because of the implemented policy, chose engineering education. It is possible that they could have contributed more to GDP growth in the alternative scenario even if they would have contributed less to Finnish patenting at the USPTO.

VI. Conclusion

Paraphrasing Jones (2005, p. 1107), the question we address is: Can we, through educational investments, increase the number of inventors, and thereby make us all richer? Furthermore, does this happen through selection or through a treatment effect? Evidence based on macrolevel studies provides at best weak evidence of a causal effect of education on growth (Krueger & Lindahl, 2001), although Aghion et al. (2009), using U.S. state-level data, find evidence of a positive effect of education on growth. To address the question directly at the microlevel, we study the link between education and invention, using a matched data set on Finnish inventors of U.S. patents for 1988 to 1996.

We find a strong positive (causal) effect of engineering education on the propensity to patent. We use a supply-side instrument—distance to the nearest engineering university as our instrument—generated from the Finnish educational policies of the period 1950 to 1981, the years in which the individuals in our sample chose their education. The first-stage result, that distance negatively affects individuals' choices, indicates that the educational policy of increasing the geographic availability of engineering education worked, in the sense that it increased the probability that individuals from the nearby regions would enter university engineering education. The interesting result is not only that the instrumental variable estimate is positive and significant, but also that the OLS bias is negative, indicating that inventive individuals may not be the typical people who would obtain a university (engineering) education, or that costs of attending university (conditional on distance) are driving selection. Our answer to the policy question is thus affirmative: yes, the number of inventors can be increased through educational policy, and the effect is not due to selection but to treatment. Our counterfactual exercise suggests that if Finland had not established the new engineering universities in the postwar era, the number of USPTO patents obtained by Finnish inventors would have been 20% lower.

Our results provide a potential explanation for the transformation of the Finnish economy, noted, for example, by Trajtenberg (2001) and analyzed by Honkapohja, Koskela, Leibfritz, and Uusitalo (2009), from a resource-based to an innovation-based economy. They also provide a potential basis for the widely adopted educational policies in countries like China and India that have invested heavily in increasing science and engineering education and to the recent U.S. worries about losing its comparative advantage in this regard. Nevertheless, we stress that the result (of us having identified an average treatment effect) leading to the policy conclusion that any policy that increases the number of engineering students also increases invention rests on relatively thin evidence. The effect of engineering education on invention may well be context and policy specific and thus not possible to generalize beyond the case examined here.

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